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(54) **HAND POINTING ESTIMATION FOR HUMAN COMPUTER INTERACTION**

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G06F 3/01 (2006.01)
G06F 3/041 (2006.01)
G06K 9/46 (2006.01)

(52) **U.S. Cl.**
CPC **G06F 3/017** (2013.01); **G06K 9/00355** (2013.01); **G06K 2009/4666** (2013.01)

(58) **Field of Classification Search**

USPC 382/100, 103, 106–107, 162, 168, 173,
382/181, 199, 209, 219, 232, 254, 274,
382/285–297, 305, 312; 345/173, 677, 163;
715/773, 784

See application file for complete search history.

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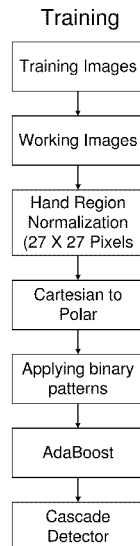
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(57) **ABSTRACT**

Hand pointing has been an intuitive gesture for human interaction with computers. A hand pointing estimation system is provided, based on two regular cameras, which includes hand region detection, hand finger estimation, two views' feature detection, and 3D pointing direction estimation. The technique may employ a polar coordinate system to represent the hand region, and tests show a good result in terms of the robustness to hand orientation variation. To estimate the pointing direction, Active Appearance Models are employed to detect and track, e.g., 14 feature points along the hand contour from a top view and a side view. Combining two views of the hand features, the 3D pointing direction is estimated.

20 Claims, 8 Drawing Sheets



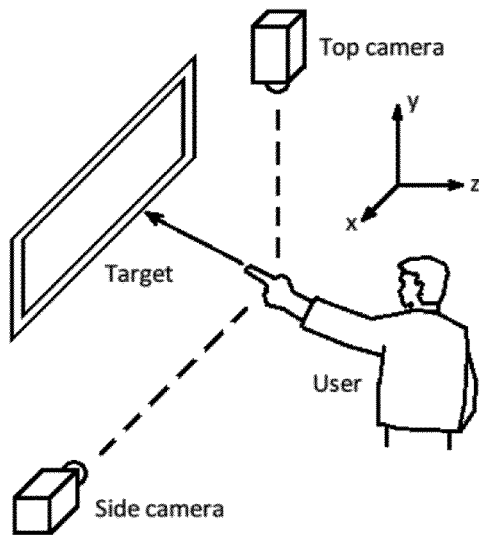


Fig. 1A

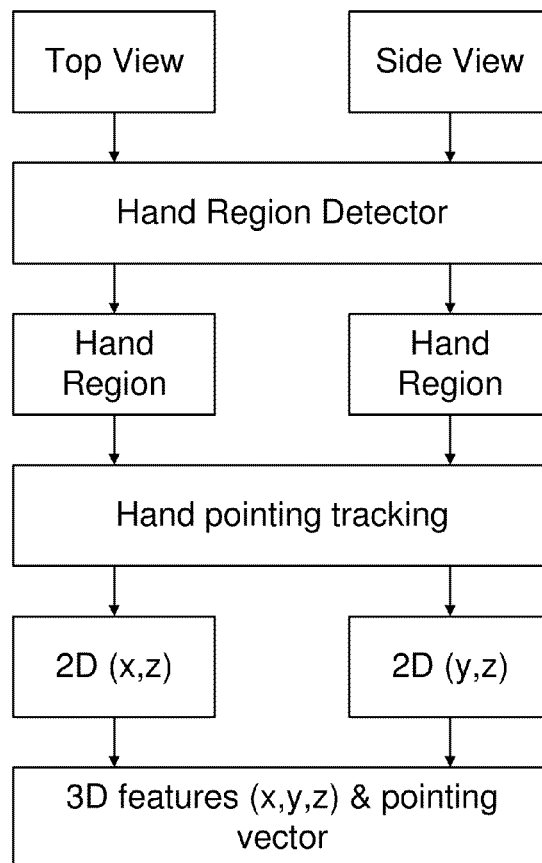


Fig. 1B

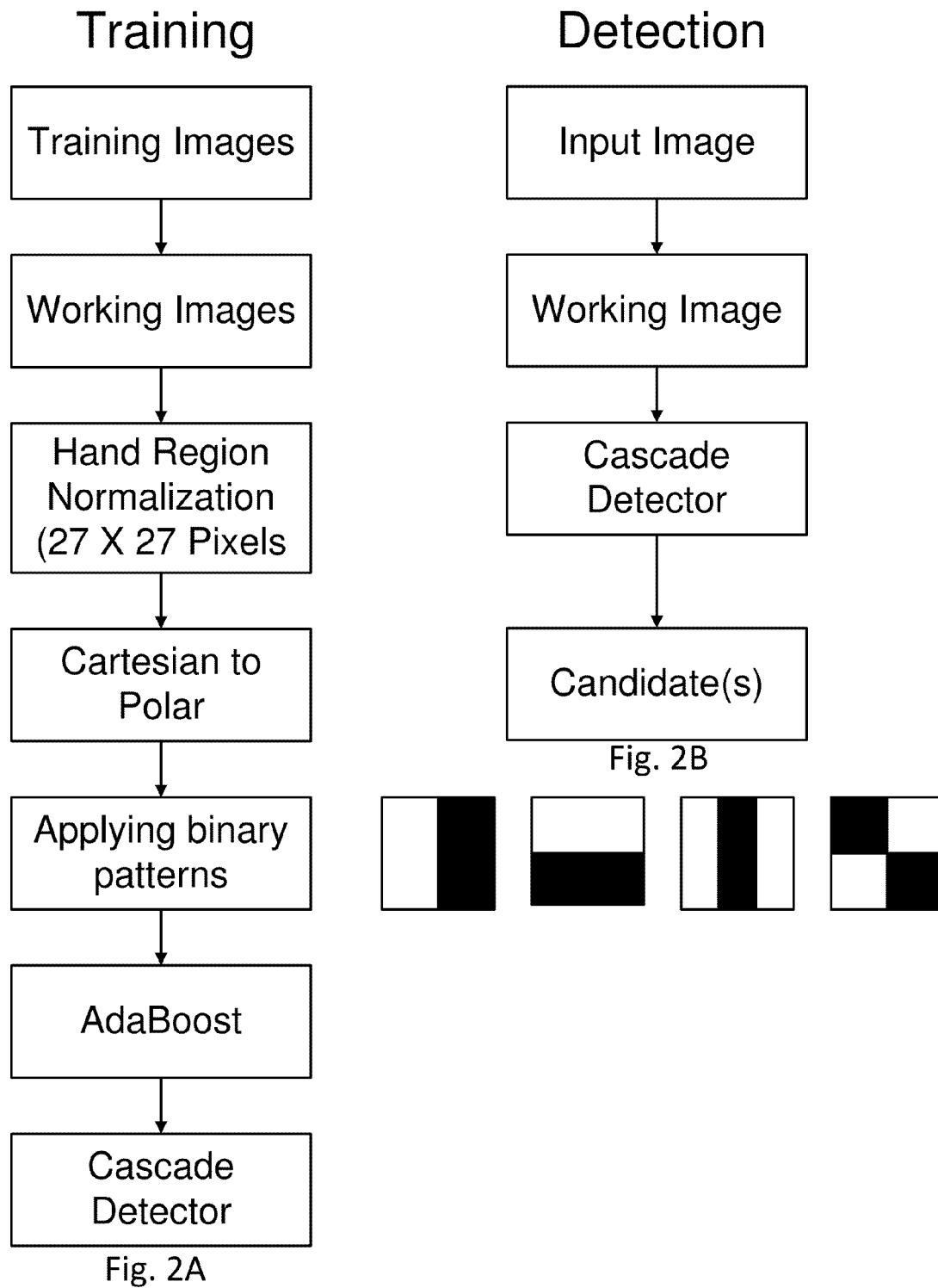




Fig. 3A



Fig. 3B

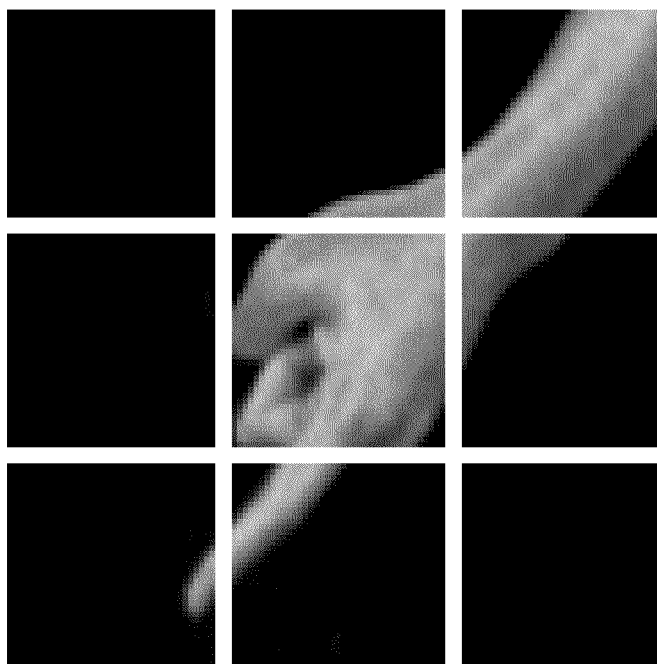


Fig. 3C



Fig. 4A

Fig. 4B

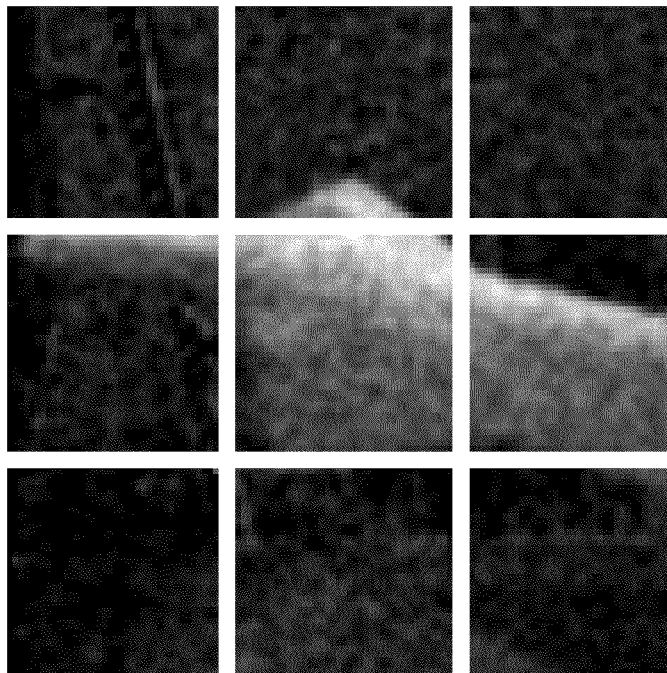


Fig. 4C

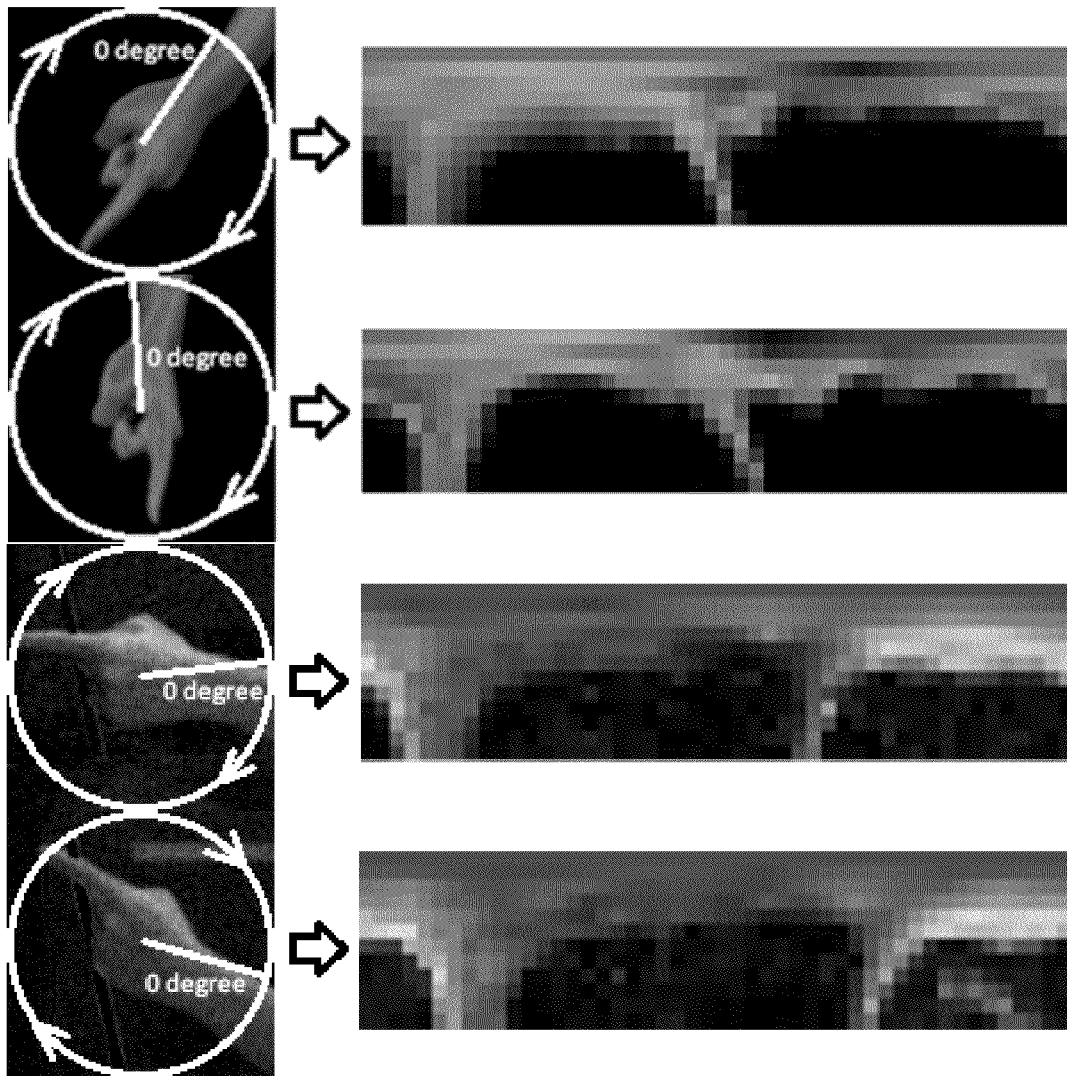


Fig. 5

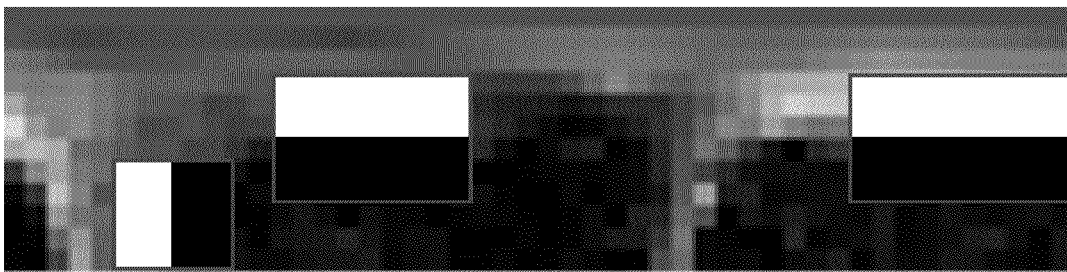


Fig. 6

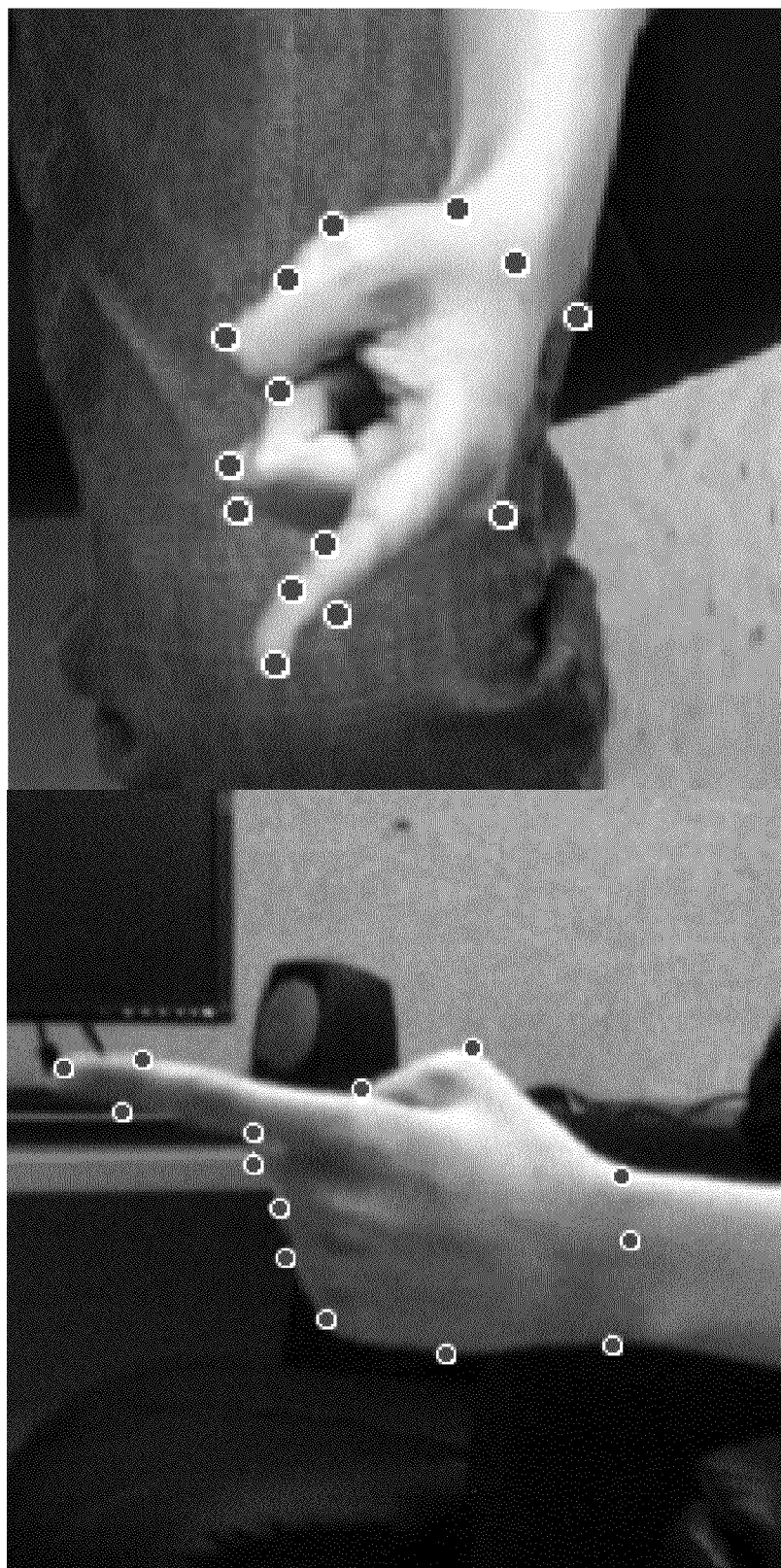


Fig. 7

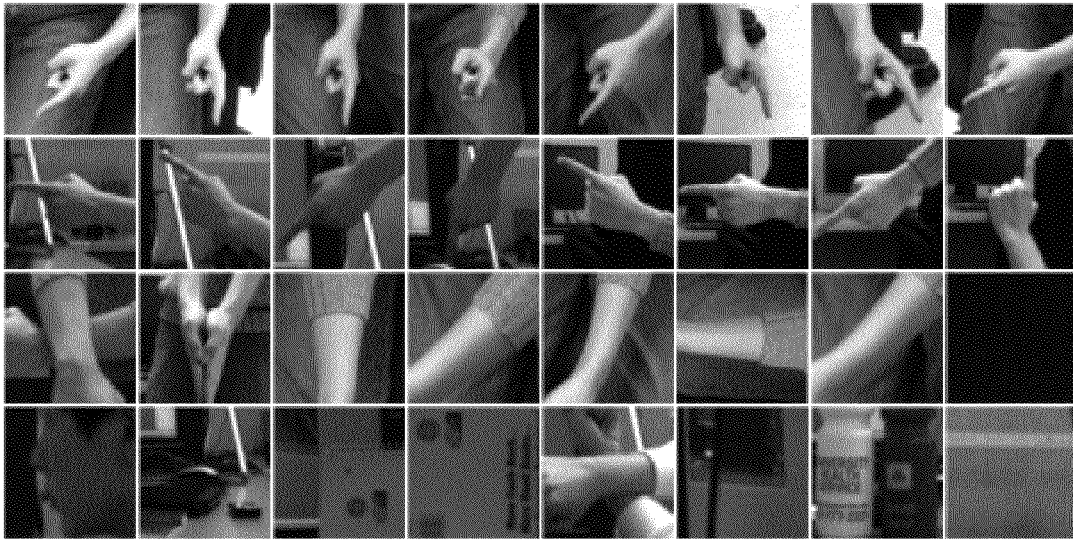


Fig. 8

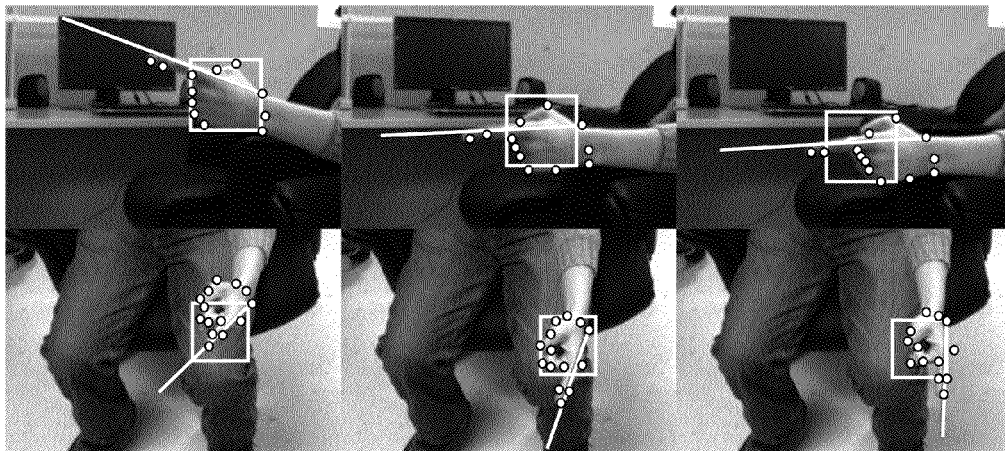
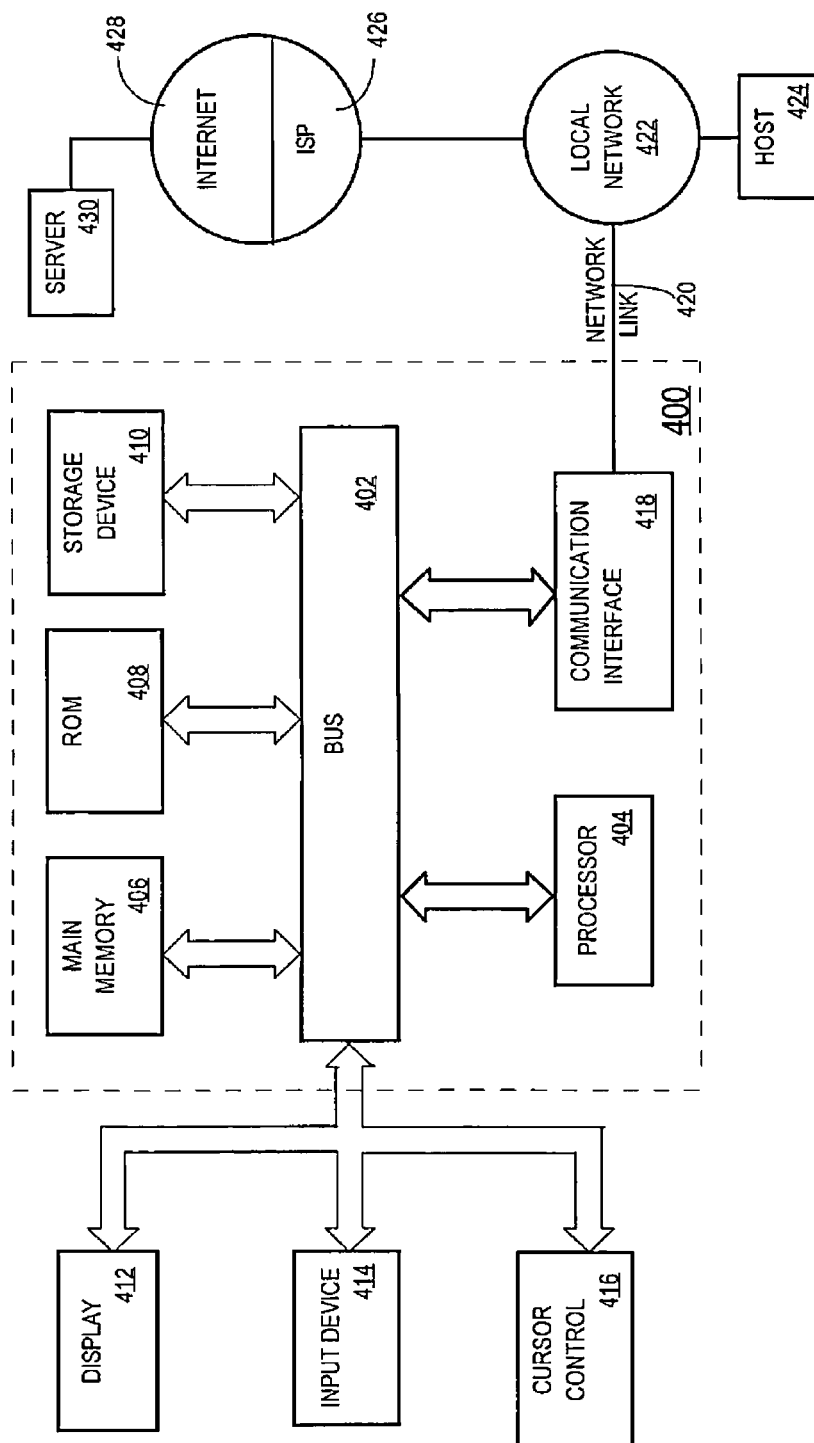


Fig. 9

Fig. 10



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HAND POINTING ESTIMATION FOR HUMAN COMPUTER INTERACTION

CROSS REFERENCE TO RELATED APPLICATION

The present application is a Continuation of U.S. patent application Ser. No. 13/571,645, filed Aug. 10, 2012, now U.S. Pat. No. 8,971,572, issued Mar. 3, 2015, which is a Nonprovisional of U.S. Provisional Patent application 61/523,152, filed Aug. 12, 2011, which is expressly incorporated herein by reference in its entirety.

STATEMENT OF GOVERNMENT RIGHTS

This work was funded by grant FA8750-08-01-0096 from the United States Air Force. The government may have certain rights in the invention.

BACKGROUND OF THE INVENTION

Hand gesture is an efficient means for humans interacting with computers [9, 13, 17]. The most basic and simplest gesture is pointing. Pointing gesture can resolve ambiguities derived from the verbal communication, thus opening up the possibility of humans interacting or communicating intuitively with computers or robots by indicating objects or pointed locations either in the three dimensional (3D) space or on the screen. However, it is a challenging task to estimate the 3D hand pointing direction automatically and reliably from the streams of video data due to the great variety and adaptability of hand movement and the undistinguishable hand features of the joint parts. Some previous work show the success in hand detection and tracking using multi-colored gloves [16] and depth-aware cameras [8], or background subtraction [14], color-based detection [7, 8], stereo vision based [2, 4, 18] or binary pattern based [5, 10] hand feature detection. However, the big challenge remains for accurate hand detection and tracking in terms of various hand rotations.

Recent advances of feature detection [1, 5, 6, 8, 10, 11, 12, 19] make possible determination of hand gestures.

An expectation minimization framework for view independent recognition of hand postures is provided in [21]. This is intended to determine a gesture, and not a pointing direction.

SUMMARY AND OBJECTS OF THE INVENTION

Hand pointing has been an intuitive gesture for human interaction with computers. Big challenges are still posted for accurate estimation of finger pointing direction in a 3D space. The present technology provides a hand pointing estimation system based on two regular cameras, which includes hand region detection, hand finger estimation, two views' feature detection, and 3D pointing direction estimation. The hand detection system has similarities to a binary pattern face detector, in which a polar coordinate system is proposed to represent the hand region, and achieved a good result in terms of the robustness to hand orientation variation. To estimate the pointing direction, an Active Appearance Model (AAM) based approach was applied to detect and track 14 feature points along the hand contour from a top view and a side view. Combining two views of the hand features, the 3D pointing direction is estimated. See, Kaoning Hu et al., "Hand Pointing Estimation for Human Computer Interaction Based on Two Orthogonal-Views", IEEE International Conference on Pattern Recognition p. 3670-3673 (2010); Reale, M. J., "A

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Multi-Gesture Interaction System Using a 3-D Iris Disk Model for Gaze Estimation and an Active Appearance Model for 3-D Hand Pointing", IEEE Transactions on Multimedia, June 2011; Air Force Research Laboratory, Information Directorate "Real Time Eye Tracking And Hand Tracking Using Regular Video Cameras For Human Computer Interaction", State University of New York at Binghamton (January 2011), Final Technical report, expressly incorporated herein by reference in their entirety.

The Active Appearance Model (AAM) is a generalization of the Active Shape Model approach, but uses all the information in the image region covered by the target object, rather than just that near modeled edges. An AAM contains a statistical model of the shape and grey-level (or by extension, color) appearance of the object of interest which can generalize to almost any valid example. Matching to an image involves finding model parameters which minimize the difference between the image and a synthesized model example, projected into the image. The model has a potentially large number of parameters. Displacing each model parameter from the correct value induces a particular pattern in the residuals. In a training phase, the AAM learns a linear model of the relationship between parameter displacements and the induced residuals. During search it measures the residuals and uses this model to correct the current parameters, leading to a better fit. A good overall match is obtained in a few iterations, even from poor starting estimates. See pages.manchester.ac.uk/staff/timothy.f.cootes/tfc_publications.html

In AAM, principal component analysis (PCA) may be used to find the mean shape and main variations of the training data to the mean shape. After finding the Shape Model, all training data objects are deformed to the main shape, and the pixels converted to vectors. Then PCA is used to find the mean appearance (intensities), and variances of the appearance in the training set. Both the Shape and Appearance Model are combined with PCA to one AAM-model. By displacing the parameters in the training set by a known amount, a model can be created that provides an optimal parameter update for a certain difference in model-intensities and normal image intensities.

It is understood that a single image plus depth information, such as available from a Microsoft Kinect (Primesense) system, or other 3D acquisition system, may be employed. See, US20120124516; US20120169583; US20120078614; US20120070070; US20120038986; US20110293137; US20110025827; US20110292036; US20110052006; US20100284082; 20100265316; US20110158508; US20110211044; US20090185274; US20100284082; U.S. Ser. No. 09/616,606; U.S. Pat. No. 6,101,269; U.S. Pat. No. 7,348,963; WO2007/043036, WO2007/132451; WO2007/105205, WO2008/120217, WO2010/004542, WO2007/043036; WO2007/105205; WO03/071410; PCT/IL2006/000335; TW 527528 B; Sazbon et al., "Qualitative Real-Time Range Extraction for Preplanned Scene Partitioning Using Laser Beam Coding," Pattern Recognition Letters 26, pages 1772-1781 (2005); Garcia et al., "Three-dimensional mapping and range measurement by means of projected speckle patterns", Applied Optics, Vol. 47, No. 16, pages 3032-3040 (2008); Garcia et al., "Projection of speckle patterns for 3D sensing", by Journal of Physics, Conference series 139 (2008), each of which is expressly incorporated herein by reference. See also U.S. Pat. No. 4,988,981; U.S. Pat. No. 4,550,250; U.S. Pat. No. 6,452,584; U.S. Pat. No. 5,549,469; U.S. Pat. No. 7,821,541; US20080256494; and WO2007/043036, each of which is expressly incorporated herein by reference. Another method of three-dimensional imaging

uses time-of-flight (TOF) information to create a dense depth map. See, US20110296353; U.S. Pat. Nos. 6,323,942; 6,515; 6,522,395; 6,614,422; 6,674,895; 6,678,039; 6,710,770; 6,906,793; 7,151,530; 7,176,438; 7,212,663; 7,321,111; 7,340,077; 7,352,454; 7,507,947, each of which is expressly incorporated herein by reference.

The present technology provides a system and method to estimate pointing direction, e.g., based on two orthogonal-view cameras, or a plurality of images representing parallax views.

A system and method for hand gesture recognition, and more particularly, according to a preferred embodiment, finger pointing direction estimation, is provided. A preferred embodiment has a high degree of robustness to hand rotation. By using multiple camera views to capture a hand, the hand can be tracked and modeled via AAM. Using the tracked points from the AAM allows inference of the 3D orientation of the pointing finger, due to the correspondence between points on the finger of both views.

In like manner, other types of gestures may be recognized. Thus, for example, the vectors or change in vectors over time, of one or more fingers or other portions of the hand and wrist may be determined or measured. Thus, multi-finger gestures or gesticulations are supported. For example, a variety of gestures involving multiple fingers are supported by Apple Corp. OSX and iOS4. See, e.g., www.apple.com/macosex/whats-new/gestures.html; support.apple.com/kb/HT3211. The present system and method may be implemented to recognize similar or corresponding gestures, among others, with or without physical contact. See also, U.S. Pat. Nos. 7,975, 242; 7,966,578; 7,957,762; 7,956,849; 7,941,760; 7,940,250; 7,934,156; 7,932,897; 7,930,642; 7,864,163; 7,844,914; 7,843,427; 7,812,828; 7,812,826; 7,800,592; 7,782,307; 7,764,274; 7,705,830; 7,688,315; 7,671,756; 7,663,607; 7,656,394; 7,656,393; 7,653,883; RE40,993; 7,619,618; 7,614,008; 7,593,000; 7,538,760; 7,511,702; 7,509,588; 7,479,949; 7,469,381; RE40,153; 7,339,580; 7,975,242; 7,966,578; 7,961,909; 7,958,456; 7,957,762; 7,956,849; 7,956,847; 7,956,846; 7,941,760; 7,940,250; 7,936,341; 7,934,156; 7,932,897; 7,932,896; 7,924,272; 7,924,271; 7,921,187; 7,920,134; 7,918,019; 7,916,126; 7,910,843; 7,907,125; 7,907,117; 7,907,020; 7,903,115; 7,902,840; 7,890,778; 7,889,185; 7,889,184; 7,889,175; 7,884,804; RE42,064; 7,877,707; 7,876,311; 7,876,288; 7,872,652; 7,870,496; 7,864,163; 7,859,521; 7,856,605; 7,844,915; 7,844,914; 7,843,427; 7,840,912; 7,835,999; 7,834,846; 7,826,641; 7,812,828; 7,812,826; 7,809,167; 7,793,228; 7,793,225; 7,786,975; 7,782,307; 7,777,732; 7,764,274; 7,760,767; 7,754,955; 7,728,821; 7,728,316; 7,719,523; 7,714,265; 7,711,681; 7,710,391; 7,705,830; 7,694,231; 7,692,629; 7,671,756; 7,667,148; 7,663,607; 7,657,849; 7,656,394; 7,656,393; 7,653,883; 7,633,076; RE40,993; 7,619,618; 7,614,008; 7,599,520; 7,593,000; 7,574,672; 7,538,760; 7,511,702; 7,509,588; 7,480,870; 7,479,949; 7,469,381; RE40,153; 7,339,580; 7,030,861; 6,888,536; 6,323,846; 20110163955; 20110157029; 20110145863; 20110145768; 20110145759; 20110145739; 20110141142; 20110141031; 20110102464; 20110080361; 20110080360; 20110080344; 20110078624; 20110078622; 20110078597; 20110078560; 20110074830; 20110074828; 20110074710; 20110074699; 20110074698; 20110074697; 20110074696; 20110074695; 20110074694; 20110074677; 20110072394; 20110072375; 20110069017; 20110069016; 20110063224; 20110055317; 20110010672; 20110010626; 20110001706; 20100313157; 20100313125; 20100309155; 20100309154; 20100309149; 20100309148; 20100309147; 20100293462; 20100289754; 20100283747; 20100273139; 20100235794;

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In addition to the described techniques, the system may be made more robust by modeling illumination patterns, and processing the images to with respect to the illumination patterns, on one hand, or normalizing the illumination pattern to make the subsequent processing generally illumination invariant. Another embodiment provides structured lighting, in order to permit direct exploitation of the illumination pattern in determining hand gestures. Another embodiment provides semistructured lighting, such as different color light from different directions, to create distinct parallax shadows and facilitate surface estimation.

According to a still further embodiment, the images are processed globally.

The present system and method also provides a model for pointing cursor determination on a screen, and evaluating the pointing direction and its error by measuring the difference between the projected positions and the expected positions on the screen. Other types of feedback may also be used to correct the algorithm and/or the output of the system.

While a preferred embodiment employs traditional 2D image sensors, 3D hand models can be captured using a 3D imaging system, such as a stereoscopic camera, structured lighting image acquisition system, such as the Microsoft Kinect or Kinect V2 (Primesense), or the like; however, a higher resolution image acquisition system (e.g., 1080P) is typically preferred for accuracy and reliability.

While one embodiment describes two orthogonal cameras, other implementations are possible. For example, a larger number of cameras, and/or cameras with different relative orientations with respect to the hand may be provided. Further, a stream of images from one or more cameras may be

provided to permit processing of hand movements over time, potentially permitting use of a single imager.

In order to generate the working image, the background of the image is first eliminated, using for example the following color channel arithmetic:

$$I(x,y)=R(x,y)-\text{Max}\{G(x,y),B(x,y)\}$$

A preferred process includes a hand image warping step. The hand-wrist junction may be estimated based on the strong correlation of skin colors between hand and wrist. In particular, the average color of the block containing the wrist is the most similar to the average color of the central block among the 8 surrounding blocks. In some cases, lighting may be controlled to accentuate this difference. Likewise, in some cases, a camera with infrared sensitivity may be employed to provide hyperspectral imaging.

In the hand image warping, the image is warped from a Cartesian to Polar space. After this warping or transformation, a binary pattern-based hand detection algorithm may be employed, for example, based on Viola-Jones' approach, using Haar-Like patterns applied to the warped image. In this process, an integral image is generated, and then Haar-like features generated using binary patterns, e.g., as shown in FIG. 2A. A cascade detector is built using AdaBoost, and an Active Appearance Model (AAM) applied. A static model may be created for each view. According to a preferred embodiment, 14 landmarks are chosen and employed for each model. The AAM may in some cases be developed based on generic human anatomy, however, development of the AAM for a particular user is preferred.

A top and side camera may be used to acquire the images, with the top view was used as (x, z) coordinates, and side view was used as (z, y) coordinates. The average of both z values may be taken to be the estimated z coordinate. Alternately, if one of the side to top cameras is known to present a better estimate of z than the average, that one camera (or some other weighed combination of the images) employed. The pointing vector was created by connecting 2 reliable landmark points on the index finger by a line.

The complex nature of the range of colors which constitute skin tones make it difficult to establish a firm set of values for image segmentation, and many types of methods for handling skin detection have been proposed. Variations in lighting further complicate the process of distinguishing skin from background colors. For these reasons, it is desirable to use machine learning approaches to establish a classifier which could accurately classify known examples of each class as well as provide reasonable guesses for colors not found in the training data.

A Bayesian classifier provides a simple, robust classification with a built-in classification confidence and can be used if a probability distribution function (PDF) can be established for each class. Since the actual PDF for the skin and background classes is not known, it is necessary to design an approximation of the PDF based on known data.

A Gaussian Mixture Model (GMM) provides such an approximation. Therefore, the basis for hand detection is a Gaussian Mixture Model (GMM) based classifier for distinguishing skin colored pixels from background pixels. This is combined with a connected component analysis system in order to locate blocks of the image which contain significant amounts of skin colored pixels.

A skin tone pixel segmentation algorithm may use a single Bayesian classifier based on the GMMs determined from a static set of training data. The classifier is fully computed ahead of time by a training program which processes a set of example images to extract the user-specified color compo-

nents and train the GMMs accordingly. Once the training program has completed, the classifier remains fixed, and can be used for a separate hand detection application. The features that were used by the classifier were taken from the YIQ color space. Like the HSV color space, YIQ consists of one component (Y) which corresponds to overall brightness, while the other two components (IQ) provide the color. By discarding the brightness component from the YIQ data, a certain degree of lighting invariance was gained.

To fit the specifications of a GMM to a set of data, a fixed number of Gaussians for the GMM were established, and then fit each of the Gaussians using the classic Expectation-Maximization (EM) algorithm. In order to locate potential hand regions in images, the system may first use a Bayesian classifier to identify skin tone areas. While every pixel of the image may be processed by the classifier. Preferably, the hand detector may divide the image into a grid of blocks which are 8x8 pixels in size. The feature values of the pixels within each block are averaged, and these mean values are fed into the classifier. The resulting classification is then applied to all pixels within the block. The size of the block was empirically selected based on the criteria that it would sufficiently reduce processing time and that it would evenly divide common image sizes.

Once the Bayesian classifier has identified each block as either skin or background (essentially producing a down-scaled classification image), the results are scanned for connected regions consisting of blocks with a skin confidence of at least 50%. A skin-pixel based region-growing approach may be applied to detect the connected components of skin regions. Connected regions whose width or height is below an empirically derived threshold are assumed to be false positives and are discarded. Any remaining connected regions are presumed to be hands.

Since the two views of hands are tracked separately with different models, we are able to create the best fit for the corresponding hand in each frame. There is correspondence between multiple landmarks in the separate views. Those landmarks, most notably on the finger, allow us to infer the 3D coordinates from 2D coordinates, and infer the 3D orientation of the finger. For one point that has correspondence between the two models, we can use the top view as the (x, z) coordinate and the side view as the (z, y) coordinate. We can then combine both of the views to infer the (x, y, z) coordinate for that tracked landmark. We use the z coordinate from the top view.

Once we have the 3D coordinates of the tracked points we take two points on the finger that are "connected by a line" to create a vector that points in the direction of the finger. The two points selected are near the top and bottom of the pointing finger. These were selected as they appear to give us the most reliable vector in determining the orientation of the finger.

Since cursor movement even with a mouse is all relative (rather than absolute) motion, we normalize the pointing vector and map the x and y components directly onto the screen. When the AAM first initializes, we record the starting z position of the hand from the top view; if the user moves his/her hand forward by a certain distance from that starting z position, we may interpret this as a mouse click.

It is therefore an object to provide a method for estimating a finger pointing direction using an active appearance model, which tracks a plurality of landmarks on the hand, corresponding to landmarks of hands in a training image set to which a principal component analysis is applied to formulate a statistical model of the hand, comprising: detecting a hand in each of at least two images acquired from different angles, locating a center of the hand and a position of the wrist in each

image; warping the detected hand in each image from a Cartesian Coordinate representation to a Polar Coordinate representation, with the center of the hand at the pole, and the polar angle determined by a position of the wrist with respect to the center of the hand; applying the active appearance model to find a best fit for visible landmarks of the hand in each image; combining the best fit for the visible landmarks of the hand in each image to the active appearance model to infer a three dimensional position of each visible landmark in each image; determining at least two visible features of a finger extending from the hand, to define a pointing gesture in each image; and determining at least one of a three dimensional pointing vector of the finger and a target of the pointing gesture.

It is a further object to provide a method for estimating a finger pointing direction using an active appearance model, which tracks a plurality of landmarks on the hand, corresponding to landmarks of hands in a training image set to which a principal component analysis is applied to formulate a statistical model of the hand, comprising: capturing at least two images of a hand from different directions; detecting the hand in each image and locating a center of the hand; determining a position of the wrist in each image; warping the detected hand in each image from a Cartesian Coordinate representation to a Polar Coordinate representation, with the center of the hand at the pole, and the polar angle determined by a position of the wrist with respect to the center of the hand; applying the active appearance model to find a best fit for the hand in each image; combining the fit of the hand in each image to the active appearance model to infer a three dimensional position of each visible point in an image; determining two points at different distances along a finger extending from the hand, to define a pointing vector in the at least two images, wherein the two points are selected based on a reliability of the resulting vector; and determining a three dimensional pointing vector of the finger.

It is a still further object to provide an apparatus for estimating a finger pointing direction, comprising: a memory configured to store parameters of an active appearance model of a hand, which includes a plurality of landmarks on the hand, corresponding to landmarks of hands in a training image set to which a principal component analysis is applied; an input configured to receive at least two images acquired from different angles; at least one processor configured to receive the input, access the memory, and produce an output based on the at least two images and the parameters in the memory; and an output port, communicating data responsive to a finger pointing direction of the hand, wherein the at least one processor is further configured to: detect a hand in each of the at least two images acquired from different angles, locating a center of the hand and a position of the wrist in each image; warp the detected hand in each image from a Cartesian Coordinate representation to a Polar Coordinate representation, with the center of the hand at the pole, and the polar angle determined by a position of the wrist with respect to the center of the hand; apply the active appearance model, based on the parameters in the memory, to find a best fit for visible landmarks of the hand in each image; combine the best fit for the visible landmarks of the hand in each image to the active appearance model to infer a three dimensional position of each visible landmark in each image; determine at least two visible features of a finger extending from the hand, to define a pointing gesture in each image; and determine a pointing direction comprising at least one of a three dimensional pointing vector of the finger and a target of the pointing gesture.

The detecting the hand may comprises generating Haar-like features from the at least two images, and implementing a cascade detector using AdaBoost, wherein portions of each

image are scanned over different translations, scales and rotations to find a best fit for the hand.

The at least two images may be color images, and color sensitive image processing may be employed to distinguish the hand from a background. Likewise, the at least two images may be color images, and color sensitive image processing may be employed to define a wrist location as a location on the hand having a most similar surrounding color consistent with skin tones.

The at least two visible features of the finger may be selected based on a reliability of a resulting three dimensional pointing vector.

The system and method may provide a user feedback display of a target of the pointing gesture and/or a target along the three dimensional pointing vector of the finger.

The determining at least one of the three dimensional pointing vector of the finger and the target of the pointing gesture may represent a statistical averaging over time derived from the pointing gesture in each image. The determined three dimensional pointing vector of the finger may represent a statistical averaging over time.

The best fit for visible landmarks of the hand in each image, or the best fit for the hand in each image, to the active appearance model may be updated for respective sequences of the at least two images, to track a movement of the hand.

The at least two images may comprise at least two video signals, each representing a time sequence of images.

BRIEF DESCRIPTION OF THE DRAWINGS

FIGS. 1A and 1B show a schematic and block diagram of major components of a preferred embodiment of the invention;

FIGS. 2A and 2B show a block diagram of hand region detection training and detection algorithms for a pair of views;

FIGS. 3A, 3B and 3C illustrate a first example of a raw image, a processed image, and a hand image divided into 3x3 blocks, respectively;

FIGS. 4A, 4B and 4C illustrate a second example of a raw image, a processed image, and a hand image divided into 3x3 blocks, respectively;

FIG. 5 shows examples of image warping from two views;

FIG. 6 illustrates an example of binary patterns overlapping on the warped image;

FIG. 7 shows landmarks for the top and side views of a hand image;

FIG. 8 shows examples of training images;

FIG. 9 shows an example of the estimated pointing vectors along with the detected hand regions and the tracked 14 feature points; and

FIG. 10 shows an exemplary hardware system according to the prior art.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

In a preferred embodiment, two regular cameras are set up in orthogonal positions, one on the top of the user, and the other to the left side.

FIGS. 1A and 1B show the major components of the system. Unlike binary-pattern based approaches [5, 10] which are limited to a certain degree of hand rotation, a hand-image warping approach is preferably provided to transform the original hand image to a polar-coordinate plane in order to make the hand detection invariant to orientation.

According to a preferred embodiment, two cascade detectors are applied based on binary pattern features and AdaBoost [15] for two views' hand region detection. Then, the Active Appearance Model (AAM) [3] is used to track the finger points to identify the direction of hand pointing. While AAM is more commonly used for face tracking, as employed herein it is extended to track landmark features of hands. The 3D orientation of a pointing finger in 2D space may then be inferred. This is done via two simultaneous or nearly simultaneous image captures of the hand, for example from two video streams with small time misalignment. The two imagers capture images of an overlapping region, in which the hand is visible. There is thus correspondence between the points in the top and side views. Using this correspondence between the points allows inference of the (x, y, z) coordinates of those points. Once the 3D coordinates are obtained, two points along the finger are used to draw a vector in 3D space, resulting in a determination of the orientation of the finger.

Hand region detection is the first step in estimating the pointing direction. FIGS. 2A and 2B show the diagram of the training algorithm and hand region detection algorithm for both views. Motivated by the success of face detection developed by Viola-Jones [15] using Haar-like features and an AdaBoost cascade detector, the corresponding features are extended to hand regions detection for the pointing gesture. The binary patterns used in [15] describe the features within facial regions with no background involved. However, the most significant features of a hand pointing gesture are the shape of the hand rather than internal hand shades and textures. As features to describe the shape of the hand pointing are desired, the visible edge and background are involved. Unfortunately, various backgrounds may cause instability for hand detection. A simple approach to solving this issue uses color channel arithmetic to reduce the influence of different types of backgrounds. By observing that the skin color has much stronger red component than the green and blue components, the image is computed by

$$I(x,y)=R(x,y)-\text{Max}\{G(x,y),B(x,y)\} \quad (1)$$

This simple process can roughly highlight the skin area. As a result, a working image I is generated, based on which subsequent operations using the binary pattern approach can be carried out effectively.

FIGS. 3A, 3B, 3C, 4A, 4B, and 4C show two examples of a captured image, processed image and a 3×3 decomposition of the hand, respectively.

Some existing work has applied pre-designed binary patterns for hand detection successfully [5, 10]. However, the detection is still sensitive to the variation of hand orientations. The report in [5] shows that only 15° of hand rotation can be detected by applying the Viola-Jones-like approach [15], resulting in a significant limitation. To improve the orientation invariance to hand region detection, the present technology warps the hand image from Cartesian coordinates to polar-radial coordinates. To do so, the center of the window is used as a pole ("0"), and the polar angle (A) at 0 degrees is determined by the position of the wrist, as shown in FIG. 5. The radius (r) of the polar axis is determined by the window size.

Since a hand is always connected with its corresponding wrist, in order to estimate the wrist position, 27×27 hand image is divided into 3×3 blocks as shown in FIGS. 3C and 4C. In these figures, the first is contained in the central block, and the wrist is located at one of the surrounding 8 blocks. Due to the strong correlation of skin colors between hand and wrist, the average color of the block containing the wrist is the most similar to the average color of the central block among

the 8 surrounding blocks. The position of the wrist is identified by comparing the average color of the 8 blocks and the central block.

After the position of the wrist is determined, this position is used as the 0 degree polar coordinate, and the image converted from Cartesian (x, y) to Polar coordinates (θ, r).

FIG. 5 shows examples of the image warping from both views. As seen, the converted images have similar appearances regardless of hand orientations rotated in the image plane.

After the image conversion, the binary patterns are applied as shown in FIG. 2A (four black-white patterns) to the warped image in (A, r) coordinates.

FIG. 6 illustrates an example of the binary patterns overlapping on the warped image.

Similar to the procedure used in [15], the present hand detector performs the following three operations:

- (1) integral image generation,
- (2) Haar-like features generation using the above binary patterns, and
- (3) building cascade detector using AdaBoost.

After the detector has been built (based on the training inputs), it scans the input image in a brute-force way. All sub-windows with different size and position in the image will be input to the detector. Once a sub-window has passed the detector, it will be marked as a candidate. This searching can be performed in parallel, and results of calculations for any one block reused or exploited for calculations required for any different scale, translation, or rotation.

The processor employed may be a traditional single or multithreaded processor, an application specific processor, a CPLD, an SIMD processor (e.g., GPU-type processor), or other known type. In many cases, a single or multicore main processor may assume the processing tasks required for determining hand gestures, as part of the user interface processing. In other cases, a coprocessor, special purpose processor, or remote processing capability (e.g., cloud computing or distributed processing) may be provided. For example, in a power-constrained system, it may be more efficient to off-load the main operating system processor from assuming the entirety of the hand gesture recognition tasks, and permit another available resource or resources to implement the function. In some cases, the off-loading may be optional or in parallel. For example, in a cell-phone or tablet, the image streams may be communicated to a WiFi router or cell site for processing of the algorithm.

A particular advantage of delegation or distribution of the human user interface input processing from the main computational processor for the system driven by the interface, is that the computational load, other than the user interface, may be relatively low while the system awaits user inputs. On the other hand, aspects of the hand or other gesture recognition may be more efficiently processed outside of the main computational processor, or the load on the main computational processor from the gesture recognition may be sufficient that significantly greater capacity is achieved by offloading. Further, it is noted that the gesture recognition aspect generally requires a camera, and therefore at least a portion of the system and method may be implemented at, or in conjunction with the camera. This, in turn, permits a processed stream of user interface input information having a relatively low data rate to be presented to the operating system or application program, rather than the raw video data from one or more cameras.

Given the detected hand regions, hand features are tracked in the limited search regions. An Active appearance model (AAM) [3] is applied to track 14 pre-defined feature hand-

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points on both top view and side view. AAM is a method of matching statistical models to images developed by Cootes et al. [3]. A set of landmark images are used to create the training set. The model parameters that control the shape and gray-level variation are subsequently learned from this training set.

The landmarks selected for the training set represent the shape of the object to be modeled. These landmarks are represented as a vector and principal component analysis is applied to them. This can be approximated with the following formulas:

$$x = \bar{x} + P_s b_s, \text{ for shape and } g = \bar{g} + P_g b_g \text{ for texture.}$$

In the shape formula \bar{x} is the mean shape. P_s represents the modes of variation and b_s defines the shape parameters. In the texture formula \bar{g} is the mean gray level. P_g represents the modes of variation and b_g defines the grey-level parameters.

AAMs are used to create a statistical model of the hand from two orthogonal views via a simultaneous capture. A separate appearance model is created for each view, and the hand tracked in two views separately. To create the hand shape and gray-level models 14 landmarks were chosen for the training set images.

These landmarks for the top and side views can be seen in FIG. 7. Note that the hand detection of the previous stage allows us to narrow down the search region for fitting our model to the hand, thus reducing the time for finding a correct fit.

Since the two views of hands are tracked separately with different models, the best fit for the corresponding hand is created for each frame. There is correspondence between multiple landmarks in the separate views. Those landmarks, most notably on the finger, allow inference of the 3D coordinates from 2D coordinates, and inference of the 3D orientation of the finger.

For one point that has correspondence between the two models, the top view can be used as the (x, z) coordinate and the side view as the (z, y) coordinate.

Both of the views may be combined to infer the (x, y, z) coordinate for that tracked landmark. Since the z coordinate may not be the same in both of the views, both values are averaged to give us a new z coordinate.

Once the 3D coordinates of the tracked points are obtained, two points on the finger that are "connected by a line" are selected to create a vector that points in the direction of the finger. The two points selected are near the top and bottom of the pointing finger. These were selected, for example, as they appear to give the most reliable vector in determining the orientation of the finger. The other landmarks are used to create a better fit for the AAM search, as well as for future modeling of hand details. This vector is shown in FIG. 9 via the line pointing from the finger.

The system may be set up with two regular cameras (i.e., color video cameras), one being a top view and the other a side view. A preferred embodiment of the system works with a resolution of 640x480. To train two detectors for two views separately, 107 positive image samples and 160 negative samples were selected for the top view of hands, and 128 positive samples and 145 negative samples selected for the side view. FIG. 8 shows examples of training images.

It is noted that the video cameras may have associated illuminators, which may emit visible or infrared light. In the case of infrared light, the system should be calibrated for the reflective characteristics of human skin under such illumination. Structured illumination may also be employed, though it is typically not necessary.

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In the training stage, the binary patterns were applied to the converted image in the polar coordinate system, and over 5,000 features generated for each sample.

Then, two views cascade detectors are built based on the feature selection by AdaBoost. In the testing stage, after the input image is converted to the working image, each detector scans the working image in each view separately. Note that during the hand region search, the integral image is computed locally on the warped image in the polar coordinate system. The experiments are conducted in our lab environment. The hand motion is in the range of $[-60^\circ, +60^\circ]$ for both pan and tilt.

FIG. 9 shows an example of the estimated pointing vectors (line) along with the detected hand regions (box) and the tracked 14 feature points (dots).

Table 1 shows the degrees of rotation of the finger pointing in FIG. 9 and their corresponding normal vectors n.

TABLE 1

Degrees of rotation for vectors in FIG. 9

Tilt (upper row)	20.6°	-2.57°	-3.81°
Pan (lower row)	-45.81°	-18.94°	-1.42°
$\vec{n} = (\vec{x}, \vec{y}, \vec{z})$	(-0.58, 0.20, -0.56)	(-0.23, -0.03, -0.67)	(-0.02, -0.06, -0.99)

Comparing the detected hand regions with the manual selected ones, 90% and 91% correct detection rate was achieved for the top-view (691 images) and side view (829 images), respectively. In addition, the estimated hand pointing orientations are also compared to the physically measured hand orientation during the time of capture. Among 7,600 frames, 6,916 frames show less than 5-degree difference between two data sets. The correct pointing rate is 91%.

Hardware Overview

According to a preferred embodiment, the gaze direction determination system executes on a Microsoft Windows® system, using Windows XP, Vista or Windows 7 (64-bit), having an Intel Core-2 Duo (2.0 GHz) equivalent or greater CPU, greater than 2 GB RAM, an NVIDIA graphics card supporting CUDA 3.1.9 or greater, at least 300 MB free hard disk, and a USB webcam.

FIG. 10 (see U.S. Pat. No. 7,702,660, expressly incorporated herein by reference), shows a block diagram that illustrates a computer system 400 upon which an embodiment may be implemented. Computer system 400 includes a bus 402 or other communication mechanism for communicating information, and a processor 404 coupled with bus 402 for processing information. Computer system 400 also includes a main memory 406, such as a random access memory (RAM) or other dynamic storage device, coupled to bus 402 for storing information and instructions to be executed by processor 404. Main memory 406 also may be used for storing temporary variables or other intermediate information during execution of instructions to be executed by processor 404. Computer system 400 further includes a read only memory (ROM) 408 or other static storage device coupled to bus 402 for storing static information and instructions for processor 404. A storage device 410, such as a magnetic disk or optical disk, is provided and coupled to bus 402 for storing information and instructions. The computer system may also employ non-volatile memory, such as FRAM and/or MRAM.

The computer system may include a graphics processing unit (GPU), which, for example, provides a parallel processing system which is architected, for example, as a single instruction-multiple data (SIMD) processor. Such a GPU may be used to efficiently compute transforms and other

readily parallelized and processed according to mainly consecutive unbranched instruction codes.

Computer system **400** may be coupled via bus **402** to a display **412**, such as a liquid crystal display (LCD), for displaying information to a computer user. An input device **414**, including alphanumeric and other keys, is coupled to bus **402** for communicating information and command selections to processor **404**. Another type of user input device is cursor control **416**, such as a mouse, a trackball, or cursor direction keys for communicating direction information and command selections to processor **404** and for controlling cursor movement on display **412**. This input device typically has two degrees of freedom in two axes, a first axis (e.g., x) and a second axis (e.g., y), that allows the device to specify positions in a plane.

As discussed above, the present technology provides an alternate or supplemental user input system and method, which may advantageously be used in conjunction with other user interface functions which employ the same camera or cameras.

The technology is related to the use of computer system **400** for implementing the techniques described herein. According to one embodiment, those techniques are performed by computer system **400** in response to processor **404** executing one or more sequences of one or more instructions contained in main memory **406**. Such instructions may be read into main memory **406** from another machine-readable medium, such as storage device **410**. Execution of the sequences of instructions contained in main memory **406** causes processor **404** to perform the process steps described herein. In alternative embodiments, hard-wired circuitry may be used in place of or in combination with software instructions for implementation. Thus, embodiments of are not limited to any specific combination of hardware circuitry and software.

The term “machine-readable medium” as used herein refers to any medium that participates in providing data that causes a machine to operation in a specific fashion. In an embodiment implemented using computer system **400**, various machine-readable media are involved, for example, in providing instructions to processor **404** for execution. Such a medium may take many forms, including but not limited to, non-volatile media, volatile media, and transmission media. Non-volatile media includes, for example, semiconductor devices, optical or magnetic disks, such as storage device **410**. Volatile media includes dynamic memory, such as main memory **406**. Transmission media includes coaxial cables, copper wire and fiber optics, including the wires that comprise bus **402**. Transmission media can also take the form of acoustic or light waves, such as those generated during radio-wave and infra-red data communications. All such media must be tangible to enable the instructions carried by the media to be detected by a physical mechanism that reads the instructions into a machine. Wireless or wired communications, using digitally modulated electromagnetic waves are preferred.

Common forms of machine-readable media include, for example, hard disk (or other magnetic medium), CD-ROM, DVD-ROM (or other optical or magnetooptical medium), semiconductor memory such as RAM, PROM, EPROM, FLASH-EPROM, any other memory chip or cartridge, a carrier wave as described hereinafter, or any other medium from which a computer can read. Various forms of machine-readable media may be involved in carrying one or more sequences of one or more instructions to processor **404** for execution.

For example, the instructions may initially be carried on a magnetic disk of a remote computer. The remote computer can load the instructions into its dynamic memory and send the instructions over the Internet through an automated computer communication network. An interface local to computer system **400**, such as an Internet router, can receive the data and communicate using a wireless Ethernet protocol (e.g., IEEE-802.11n) to a compatible receiver, and place the data on bus **402**. Bus **402** carries the data to main memory **406**, from which processor **404** retrieves and executes the instructions. The instructions received by main memory **406** may optionally be stored on storage device **410** either before or after execution by processor **404**.

Computer system **400** also includes a communication interface **418** coupled to bus **402**. Communication interface **418** provides a two-way data communication coupling to a network link **420** that is connected to a local network **422**. For example, communication interface **418** may be an integrated services digital network (ISDN) card or a modem to provide a data communication connection to a corresponding type of telephone line. As another example, communication interface **418** may be a local area network (LAN) card to provide a data communication connection to a compatible LAN. Wireless links may also be implemented. In any such implementation, communication interface **418** sends and receives electrical, electromagnetic or optical signals that carry digital data streams representing various types of information.

Network link **420** typically provides data communication through one or more networks to other data devices. For example, network link **420** may provide a connection through local network **422** to a host computer **424** or to data equipment operated by an Internet Service Provider (ISP) **426**. ISP **426** in turn provides data communication services through the world wide packet data communication network now commonly referred to as the “Internet” **428**. Local network **422** and Internet **428** both use electrical, electromagnetic or optical signals that carry digital data streams. The signals through the various networks and the signals on network link **420** and through communication interface **418**, which carry the digital data to and from computer system **400**, are exemplary forms of carrier waves transporting the information.

Computer system **400** can send messages and receive data, including program code, through the network(s), network link **420** and communication interface **418**. In the Internet example, a server **430** might transmit a requested code for an application program through Internet **428**, ISP **426**, local network **422** and communication interface **418**.

The received code may be executed by processor **404** as it is received, and/or stored in storage device **410**, or other non-volatile storage for later execution.

U.S. 2012/0173732, expressly incorporated herein by reference, discloses various embodiments of computer systems, the elements of which may be combined or subcombined according to the various permutations.

In this description, several preferred embodiments were discussed. It is understood that this broad invention is not limited to the embodiments discussed herein, but rather is composed of the various combinations, subcombinations and permutations thereof of the elements disclosed herein. The invention is limited only by the following claims.

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What is claimed is:

1. A method for estimating a finger pointing direction, comprising:
 - providing an active appearance model of an object of interest, comprising a statistical model of a shape and image intensity of the object of interest, the object of interest being a hand comprising the finger, which tracks a plurality of landmarks on the hand, derived from characteristics of a plurality of different hands, in a memory;
 - receiving a plurality of images acquired from different angles representing a hand having at least one finger having a finger pointing direction;
 - detecting the hand in each of the plurality of images;
 - locating a center of the hand in each of the plurality of image;
 - locating a position of a wrist proximate to the hand in each of the plurality of image;
 - processing the plurality of images with an automated processor to warp the detected hand in each image from a Cartesian Coordinate representation to a Polar Coordinate representation, with the located center of the hand at the pole, and the polar angle determined by the determined location of the wrist proximate to the hand with respect to the center of the hand;
 - applying the active appearance model to find a best fit for visible landmarks of the hand in each of the plurality of

images, comprising at least two visible features of the at least one finger having the finger pointing direction; combining the best fit for the visible landmarks of the hand in each of the plurality of images to the active appearance model, to infer a three dimensional position of each visible landmark in each of the plurality of images; and determining the pointing direction of the at least one finger having the finger pointing direction.

2. The method according to claim 1, wherein the detecting the hand comprises generating Haar-like features from the at least two images, and implementing a cascade detector using AdaBoost, wherein portions of each image are scanned over different translations, scales and rotations to find a best fit for the hand.

3. The method according to claim 1, wherein the plurality of images are color images, and wherein color sensitive image processing is employed to distinguish the hand from a background.

4. The method according to claim 1, wherein the plurality of images are color images, and wherein color sensitive image processing is employed to define a wrist location as a location on the hand having a most similar surrounding color consistent with skin tones.

5. The method according to claim 1, wherein the at least two visible features of the finger are selected based on a reliability of a resulting three dimensional pointing vector.

6. The method according to claim 1, further comprising providing a user feedback display of a target of the pointing gesture.

7. The method according to claim 1, wherein the determining the pointing direction of the at least one finger having the finger pointing direction comprises determining the pointing direction of the at least one finger having the finger pointing direction in each of the plurality of images, and the determining a target of the finger pointing direction by at least statistically averaging the determined pointing direction for each of the plurality of images over time.

8. The method according to claim 1, wherein a best fit for visible landmarks of the hand in each of the plurality of images to the active appearance model is updated for respective sequences of the plurality of images, to track a movement of the hand over time.

9. The method according to claim 1, wherein the plurality of images comprise at least two video signals, each representing a time sequence of images.

10. A method for estimating a finger pointing direction using an active appearance model of an object of interest, comprising a statistical model of a shape and image intensity of the object of interest, the object of interest being a hand comprising the finger, which tracks a plurality of landmarks on a hand, corresponding to landmarks of hands in a training image set to which a principal component analysis is applied to formulate a statistical model of the hand, comprising:

capturing a plurality of images of a hand from different perspectives;

locating a center of the hand in each image with at least one automated processor;

determining a position of a wrist associated with the hand in each image with the at least one automated processor;

converting a representation of the hand in each image from a Cartesian Coordinate representation to a Polar Coordinate representation with the at least one automated processor, with the center of the hand at the pole of the Polar Coordinate representation, and the polar angle determined by a position of the wrist with respect to the located center of the hand;

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finding a best fit for the hand in each image to the active appearance model of the object of interest with the at least one automated processor;

inferring a three dimensional position of a plurality of landmarks on the hand, comprising at least two landmarks on a finger making a pointing gesture, in each image, with the at least one automated processor;

combining the fit of the hand to the active appearance model of the object of interest in each image, with the inferred three dimensional position of a plurality of landmarks on the hand, comprising at least two landmarks on a finger making a pointing gesture, to determine a pointing vector of the finger making a pointing gesture in each of the images, with the at least one automated processor, wherein the at least two landmarks on the finger making the pointing gesture are selected based on an estimated reliability of the resulting vector; and

determining a three dimensional pointing vector of the finger based on the determined pointing vector of the finger making a pointing gesture in each of the images with the at least one automated processor.

11. The method according to claim 10, wherein the hand is detected in the plurality of images by at least generating Haar-like features from the a plurality of images, and implementing a cascade detector using AdaBoost, wherein portions of each image are scanned over different translations, scales and rotations to find a best fit for the hand.

12. The method according to claim 10, wherein the a plurality of images are color images, and wherein color sensitive image processing is employed to distinguish the hand from a background, and color sensitive image processing is employed to define a wrist location as a location on the hand having a most similar surrounding color consistent with skin tones.

13. The method according to claim 10, wherein the at least two landmarks on the finger making the pointing gesture are selected independently from at least three landmarks of the finger making the pointing gesture, in each of the plurality of images based on the estimated reliability of a resulting three dimensional pointing vector.

14. The method according to claim 10, further comprising providing, with the at least one automated processor, a user feedback display of a target along the three dimensional pointing vector of the finger.

15. The method according to claim 10, wherein the determined three dimensional pointing vector of the finger represents a statistical averaging over time.

16. The method according to claim 10, wherein the best fit for the hand in each image to the active appearance model of the object of interest is updated for respective sequences of the plurality of images by the at least one automated processor, to track a movement of the hand.

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17. The method according to claim 10, wherein the plurality of images comprise a plurality of video signals, each representing a time sequence of images.

18. An apparatus for estimating a finger pointing direction, comprising:

a memory configured to store an active appearance model of an object of interest, comprising a statistical model of a shape and image intensity of the object of interest, the object of interest being a hand comprising the finger, which tracks a plurality of landmarks on the hand, derived from characteristics of a plurality of different hands;

at least one input port configured to receive a plurality of images acquired from different angles representing a hand having at least one finger having a finger pointing direction;

at least one automated processor, configured to:
detect the hand in each of the plurality of images;
locate a center of the hand in each of the plurality of image;
locate a position of a wrist proximate to the hand in each of the plurality of image;

process the plurality of images with an automated processor to warp the detected hand in each image from a Cartesian Coordinate representation to a Polar Coordinate representation, with the located center of the hand at the pole, and the polar angle determined by the determined location of the wrist proximate to the hand with respect to the center of the hand;

apply the active appearance model of the object of interest to find a best fit for visible landmarks of the hand in each of the plurality of images, comprising at least two visible features of the at least one finger having the finger pointing direction;

combine the best fit for the visible landmarks of the hand in each of the plurality of images to the active appearance model of the object of interest, to infer a three dimensional position of each visible landmark in each of the plurality of images; and

determine the pointing direction of the at least one finger having the finger pointing direction.

19. The apparatus according to claim 18, further comprising a port configured to present information defining a target of the finger pointing direction.

20. The apparatus according to claim 18, wherein the plurality of images are color images, and wherein the at least one processor is further configured to:

perform color sensitive image processing to distinguish the hand from a background; and

detect the hand by generating Haar-like features from the a plurality of images, and implementing a cascade detector using AdaBoost, wherein portions of each image are scanned over different translations, scales and rotations to find a best fit for the hand.

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